



# **Artificial Intelligent Control of Permanent Magnet Synchronous Generator Based Wind Energy Conversion System**

Maher Faeq Mohammed

Department of Electronic and Control, Technical College of Kirkuk, North Technical University,  
Kirkuk, Iraq.

[maher\\_usm@yahoo.com](mailto:maher_usm@yahoo.com)

## **Abstract**

In this work new maximum power extracted architecture is proposed for wind turbine generator. Adaptive network based fuzzy inference system (ANFIS) is used to precisely estimate the rotor angle and speed which is necessary for vector control in order to forces the generator to track maximum power using variable speed operation generator. In this algorithm the separate control of the torque from the flux make the control of a generator operation with variable speed more efficient. The ANFIS network is trained off line from the normal operation of the permanent magnet generator.

**Keywords:** Artificial intelligent, Permanent magnet, Synchronous generator, Wind energy.

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## التحكم الذكي الاصطناعي لمولد متزامن ذو مغناطيس دائم بالاعتماد على تحويل طاقة الرياح

ماهر فائق محمد

قسم الالكترونيات والسيطرة، الكلية التقنية كركوك، الجامعة التقنية الشمالية، كركوك، العراق.

[maher\\_usm@yahoo.com](mailto:maher_usm@yahoo.com)

### الملخص

في هذا العمل تم اقتراح معمارية جديدة لاستخلاص اعلى قدرة لمولدات توربينات الرياح. تم استخدام شبكة تحقيق ضبابية متكيفة لتخمين زاوية وسرعة الروتور بدقة عالية والذي هو ضروري للسيطرة الاتجاهية لجعل المولد يتتبع اعلى قدرة من السرعات المختلفة. في هذه الخوارزمية السيطرة المنفصلة للعزم عن الفيض المغناطيسي يجعل السيطرة على المولد يعمل بكفاءة عالية عند السرعات المختلفة. تم تدريب شبكة التحقيق الضبابية المتكيفة بصورة منفصلة من خلال الاشتغال الاعتيادي لمولد المغناطيس الدائم.

الكلمات الدالة: الذكاء الاصطناعي، المغناطيس الدائم، المولدات التزامنية، طاقة الرياح.

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## 1. Introduction:

Wind energy power has obtained the most important interesting in the field of renewable energy. In some areas of Iraq it is possible to build small to medium wind energy farm with a good economic feasibility. It is well known that wind energy is fluctuating over time. So that the stable and efficient use of this energy is still an open challenge for the engineers. Traditionally in the past induction generators have been used in variable speed wind power generation, but after the huge development in the permanent magnet technology, the permanent magnet synchronous generators is sweep the wind power generation markets as a results of the high efficiency of this machines. To obtain maximum power from wind turbine at variable wind speed and to reduce the effect of the flicker problem the generator must be operated at variable speed by correct adjusting the shaft speed [1,2]. The variable-speed wind turbine generation system can be operated at maximum power operating points over a wide speed range by optimally controlling the shaft speed. Traditionally vector control was used to extract maximum power for different wind speed. This algorithm proved effective performance except for one flaw it needs to know the rotor position and velocity accurately.

The precise knowledge of rotor position and speed also still an open problem for the engineering. Generally two methods were used in the past, the first method by using speed and position sensor. It is obvious that this method results in to many problems such as increased in cost and complexity [4]. The second method is using estimation algorithms. References [3-5] explain the important types of these approaches based on motional EMF, Flux linkage variation and kalman filter. However all of these methods depend largely on the mathematical model of the generator. In addition some of these methods suffer from others problem, for example the performance of motional EMF is largely deterioration at low speeds. Also it is very hard to develop an accurate mathematical model for PMSG due to distortion in rotor flux distribution this situation make the performance of kalman filter and flux linkage variation inefficient. In this work, an enhance neural-fuzzy inference system (ANFIS) is proposed for rotor position and speed estimation. After off-line training this adaptive network will be able to estimate the state variable very accurately. To perform this task two networks are used one for ( $\alpha$ ) circuit and the other for ( $\beta$ ) circuit because the Mat lap limitation for one output only to train (ANFIS) network. The input- output set data for training is obtained from normal operation of permanent magnet synchronous generator.

## 2. Modeling and Analysis of Wind Turbine:

For a variable speed wind turbine the output mechanical power available from a wind turbine can be expressed as

$$P_m = \frac{1}{2} \rho A C_p(\lambda, \beta) V_\omega^3 \quad (1)$$

Where  $\rho$  and  $A$  are air density and the area swept by blades, respectively.  $V_\omega$  is the wind velocity (m/s), and  $C_p$  is called the power coefficient, and is given as a nonlinear function of the tip speed ratio (TSR)  $\lambda$  as:

$$\lambda = \frac{\omega_r r}{V_\omega} \quad (2)$$

Where  $r$  is the wind turbine blade radius,  $\omega_r$  is the turbine speed.  $C_p$  is a function of the TSR  $\lambda$  and the blade pitch angle  $\beta$ , and is general defined with:

$$C_p = 0.73 \left( \frac{151}{\lambda_i} - 0.58\beta - 0.002\beta^{2.14} - 13.2 \right) e^{-\frac{18.4}{\lambda_i}} \quad (3)$$

$$\lambda_i = \frac{1}{\frac{1}{\lambda - 0.02\beta} - \frac{0.003}{\beta^3 + 1}}$$

By using equation (3), the relation between typical  $C_p$  and  $\lambda$  curve is shown in Fig. 1 [5]. In a wind turbine, there is an optimum value of tip speed ratio  $\lambda_{opt}$  that leads to maximum power coefficient  $C_{pmax}$ , the control objective of the maximum power extraction is arrived [6],[7]. From (1) and (2), we get

$$P_{max} = \frac{1}{3\lambda_{opt}^3} \pi \rho C_{pmax} r^2 \omega_{opt}^3 \quad (4)$$

This equation shows the relationship between the turbine power and turbine speed at maximum power output. When regulating the system under the specification of maximum power output, it must be taken into account that turbine power must never be higher than generator rated power. Once generator rated power is reached at rated wind velocity, output power must be

limited. To get maximum power out of the wind we need to have a wind turbine that allows the change in rotor speed to reach optimal aerodynamic conditions. As every optimal  $C_{p_{optimal}}$  has one optimal value of tip speed ratio  $\lambda$  therefore we have to control our tip-speed according to the wind speed. This task is well known as Maximum Power Point Tracking (MPPT). To achieve an MPPT, the PMSG is required to be operated at an optimal tip speed ratio, as shown in Fig. 2. The tip speed ratio determines the PMSG rotor speed set point for a given wind speed [5].

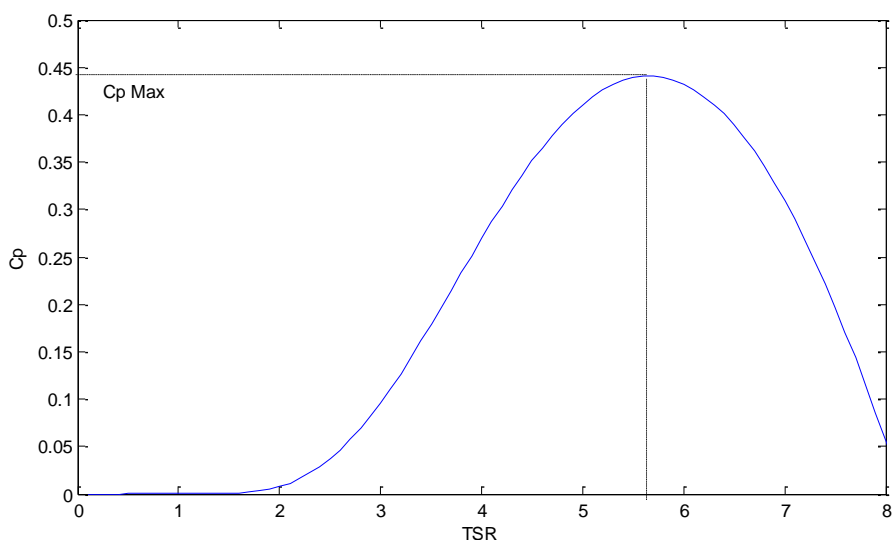


Fig. 1: Tip speed ratio TSR curve.

### 3. Control Algorithm:

To achieve maximum wind power tracking with minimum current, we need to changes the generator rotor speed set point according to the wind speed. After off line training the ANFS using a set of input-output data obtained from normal generator operation, it is used to estimate the rotor angle and speed. The difference between the estimated rotor speed with actual rotor speed is feed to the speed PI controller. The output of this speed controller give the q-axis stator current which is responsible to producing electrical torque in the permanent magnet. From Fig. 2 wind speed should be sensed in order to generate rotor reference speed ( $\omega_r^*$ ) for maximum power tracking from wind speed and the optimum tip speed ratio. To calculate rotor speed error  $\omega_{er}(n)$  at the nth sampling instant:

$$\omega_{er}(n) = \omega_r^*(n) - \hat{\omega}_r(n) \quad (5)$$

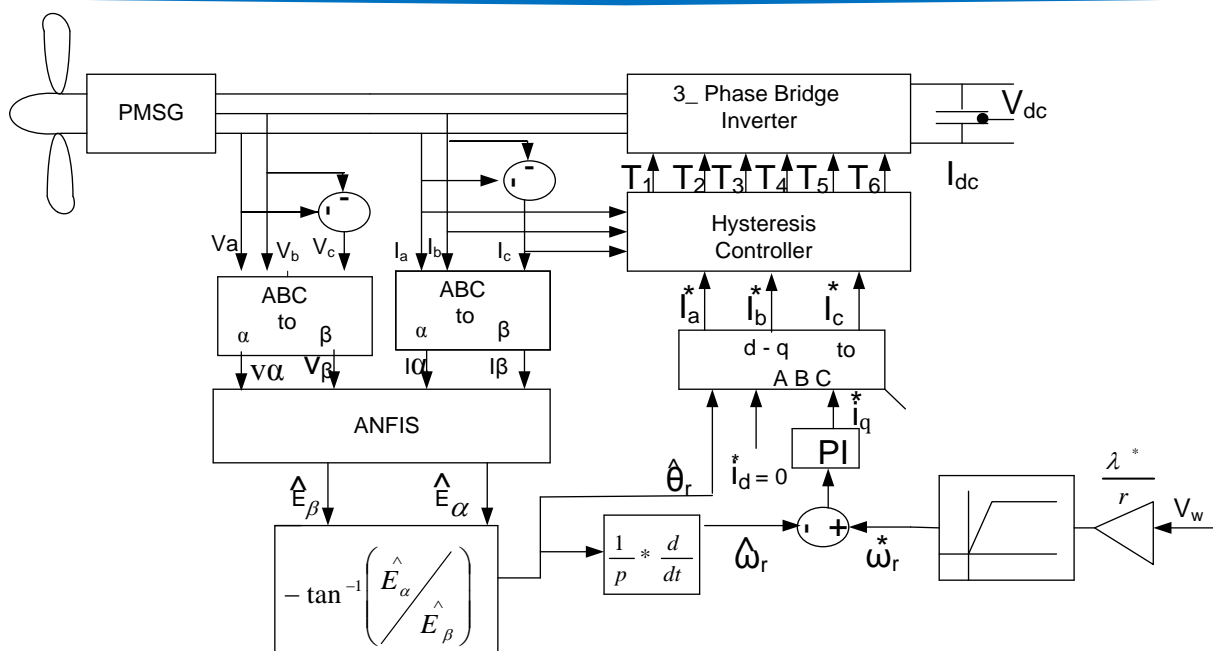


Fig. 2: Generator side control diagram.

At the  $n$ th sampling instant the output of controller gives the reference for the q-axis stator current ( $I_{qs}^*(n)$ ) as:

$$I_{qs}^* = I_{qs}(n - 1) + K_p(\omega_{er}(n) - \omega_{er}(n - 1)) + K_i\omega(n) \quad (6)$$

Where  $K_p$  and  $K_i$  are the proportional gain and integral gain respectively.

#### 4. Modeling of PMSG in Stationary Reference Frame:

The general electrical machine theory state that, in stationary reference frame the back electromotive force depends on the rotor position. So that we use this frame in this work for modeling PMSG [6] as given below:

$$V_\alpha = -R_s i_\alpha - L_s \frac{di_\alpha}{dt} + E_\alpha \quad (7)$$

$$V_\beta = -R_s i_\beta - L_s \frac{di_\beta}{dt} + E_\beta \quad (8)$$

Where  $V_{\alpha\beta}$  are stator terminal voltages,  $R_s$  is stator resistance,  $L_s$  is stator inductance,  $i_{\alpha\beta}$  are output currents and  $E_{\alpha\beta}$  are back-emf.'s which can be given as:

$$E_{\alpha\beta} = \begin{bmatrix} E_{\alpha} \\ E_{\beta} \end{bmatrix} = \omega_r \lambda_m \begin{bmatrix} -\sin(\theta_r) \\ \cos(\theta_r) \end{bmatrix} \quad (9)$$

Here  $\omega_r, \theta_r$  and  $\lambda_m$  are rotor speed, rotor position and magnetic flux linkage respectively. The details of machine equations are given in reference [6] and [12].

And finally the mechanical equations for the rotor speed and position is:

$$\frac{d\omega_r}{dt} = \frac{1}{j} (T_e - B\omega_r - T_m) \quad (10)$$

$$\frac{d\theta}{dt} = \omega_r \quad (11)$$

Where:

$$\omega_r = \text{rotor speed} \left( \frac{\text{rad}}{\text{sec}} \right)$$

$$T_e = \text{electromagnetic torque} (N.m)$$

$$J = \text{rotor inertia} (Kg.m^2)$$

$$B = \text{viscous damping} (N.m.s)$$

$$\theta = \text{rotor angle} (rad)$$

$$T_m = \text{mechinal input torque} (N.m)$$

## 5. Speed and rotor angle estimation of PMSG:

To overcome the difficulties for estimating the accurate value of back-emf from the mathematical model which is also give us the information about the rotor position and speed, an adaptive neural-Fuzzy inferred system is trained off line by using a set of input- output data obtained from normal operation of permanent magnet generator [7]. This data are the  $V_{\alpha}$  and  $i_{\alpha}$  as input data and  $E_{\alpha}$  as output data, another network is used for  $\beta$  circuit. This data is taken from a wide speed range operation of the generator, then according to The back emf equation.

$$\hat{E}_{\alpha\beta} = \begin{bmatrix} \hat{E}_{\alpha} \\ \hat{E}_{\beta} \end{bmatrix} = \hat{\omega}_r \lambda_m \begin{bmatrix} -\sin(\hat{\theta}_r) \\ \cos(\hat{\theta}_r) \end{bmatrix} \quad (12)$$

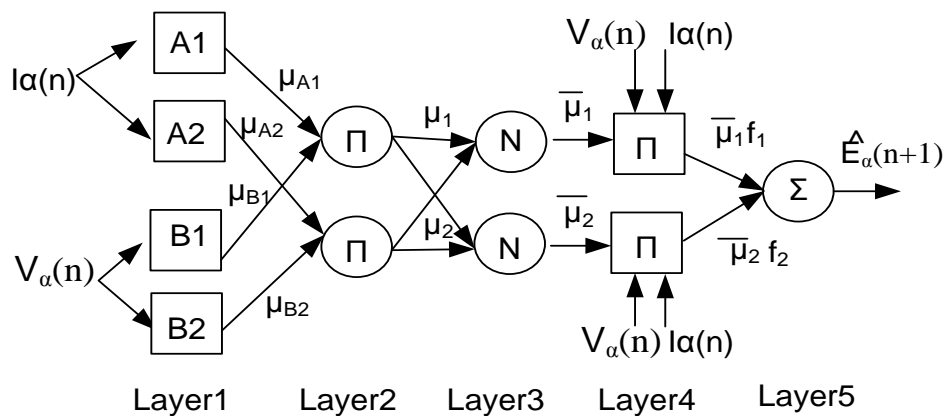
The rotor position and speed can be calculated using the estimated value of back e.m.f.'s as

$$\hat{\theta}_r = -\tan^{-1} \left( \frac{\hat{E}_\alpha}{\hat{E}_\beta} \right) \quad (13)$$

$$\hat{\omega}_r = \frac{1}{p} \frac{d\hat{\theta}_r}{dt} \quad \text{where } p \text{ is the number of poles pair} \quad (14)$$

### 6. ANFIS Architecture for Speed and Position Estimation:

As shown in Fig. 3 ANFIS using Takagi-Sugeno-Kang (TSK) inferring method having 4 : 2 : 2 : 2 : 1 structure with two inputs (currents  $i_\alpha$  and voltage  $v_\alpha$  and one outputs (estimated back e.m.f.'s  $\hat{E}_\alpha$ ) another similar network used to estimate  $E_\beta$ . The data used by ANFIS to identify PMSG is obtained from normal operation of the generator, then from equation (13) and (14) speed and position are calculated.



**Fig. 3:** ANFIS architecture for e.m.f.  $\hat{E}_\alpha$  estimation.

**Layer 1:** every node  $i$  perform fuzzyfication function [9],

$$O_{1,i} = \mu_{Ai}(I_\alpha) \quad \text{for } i=1,2$$

$$O_{2,i} = \mu_{Bi}(V_\alpha) \quad \text{for } i=1,2$$

(15)



Where  $A_i$  and  $B_i$  is a fuzzy functions associated with this node. In this work a generalized bell function is used as a membership function given by equation [11]:

$$\mu_A(x) = \left[ 1 / \left( 1 + \left| \frac{x-c_i}{a_i} \right|^{2b_i} \right) \right] \quad (16)$$

Where the value of parameters ( $a_i, b_i, c_i$ ) is the parameter set. These parameters are the target of the training process to obtain optimal form of the membership functions for fuzzy set A. Parameters in this layer are referred to as premise parameters.

**Layer 2:** In this layer the node simply multiplies the incoming input signal and forwards it to next layer .

$$\mu_i = \mu_{A_i}(X_\alpha) \cdot \mu_{B_i}(X_\beta) \quad i=1,2,3 \quad (17)$$

**Layer 3:** Every node in this layer is represented as circle. This layer calculates the normalized firing strength of each rule as given below:

$$\bar{\mu}_i = \frac{\mu_i}{\mu_1 + \mu_2 + \mu_3} \quad (18)$$

**Layer 4:** Every node in this layer is a function:

$$O_i = \bar{\mu}_i \bar{f}_i = \bar{\mu}_i (p_i I_\alpha + q_i V_\alpha + r_i) \quad i = 1,2 \quad (19)$$

This equation is the order 1 sugeno linear equation where  $\bar{\mu}_i$  is a normalized firing strength from layer 3 and  $\{p_i, q_i, r_i\}$  are the parameters set of this node. Also these parameters are the target of training algorithm to obtain optimal performance. These parameters are referred to as consequent parameters.

**Layer 5:** This layer is also called output layer which computes the output as given below:

$$\hat{E}_\alpha = \bar{\mu}_1 \cdot f_1 + \bar{\mu}_2 \cdot f_2 \quad (20)$$

The training process goes through two stage, known as precondition parameter tuning and consequent parameter tuning. Where the target is to minimize the error defined as:

$$\xi_{\alpha}^2 = (E_{\alpha} - \hat{E}_{\alpha})^2 \quad (21)$$

Where  $E_{\alpha}$  is the actual back emf obtained from normal generator operation.

To minimize the error  $\xi_{\alpha\beta}^2$  by gradient descent method, the change in each precondition parameter must be proportional to the rate of change of the error w.r.t. that preconditions parameter, i.e.

$$\Delta a_{Ai} = -\eta \frac{\partial \xi_{\alpha}^2}{\partial a_{Ai}} \quad i = 1,2,3 \quad (22)$$

Where  $\eta$  is the constant defined as the learning rate. Therefore, the new value of the consequent parameter is given as:

$$a_{Ai}(n + 1) = a_{Ai}(n) + \Delta a_{Ai} \quad i = 1,2,3$$

$$\text{Similarly} \quad b_{Ai}(n + 1) = b_{Ai}(n) + \Delta b_{Ai} \quad i = 1,2,3 \quad (23)$$

Similarly, the same procedure for consequent parameter performed on the  $\beta$  equations.

## 7. Simulation Results and Discussion:

The overall wind energy system is simulated in MATLAB/Simulink version R20014 environment using PMSG model and other necessary components from *SimPowerSystem* blockset as shown in Fig.4 with a generator rating as given in appendix A. The simulation study performs in two step training and estimation step and maximum power tracking step.

### 7.1 Training and estimation:

The first step for training is operating the generator at a wide speed range to get a set of input- output data ( $V_{\alpha}$ ,  $I_{\alpha}$  as an input  $E_{\alpha}$  output data for  $\alpha$  circuit and  $V_{\beta}$ ,  $I_{\beta}$  as input  $E_{\beta}$  output for  $\beta$  circuit) for the ANFIS network to trained off line. To test the networks performance to estimate rotor speed and angular position the system is connected as in Fig. 2 with a random trapezoidal wind velocity profile as shown in Fig. 5. Fig. 6 represents the mechanical torque input to the generator. The Actual and estimated rotor speed is shown in Fig.7 and actual and estimated rotor angle shown in Fig. 8 in this figure the time range have been reduce to 0.2 sec for the clarity. It was observed from the result the high accuracy estimation of the ANFIS network. Finally Fig. 9 shows the generator phase voltage.

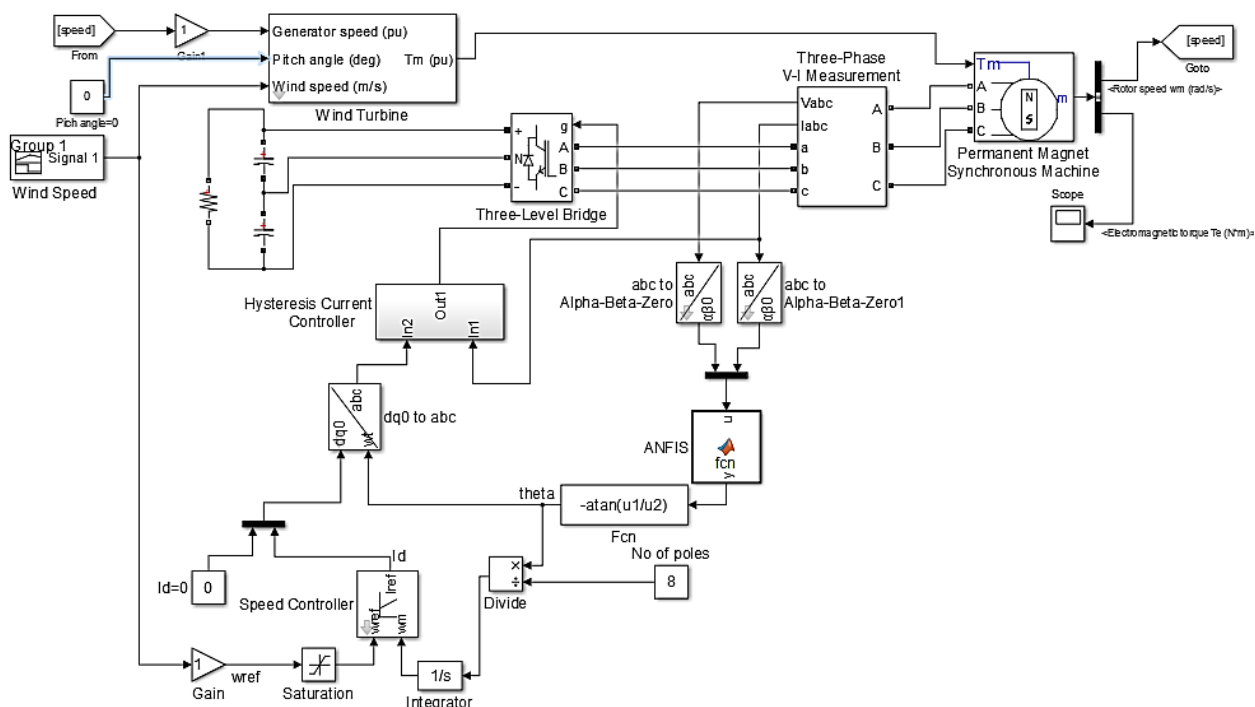


Fig. 4: Overall wind energy system in Matlab Simulink.

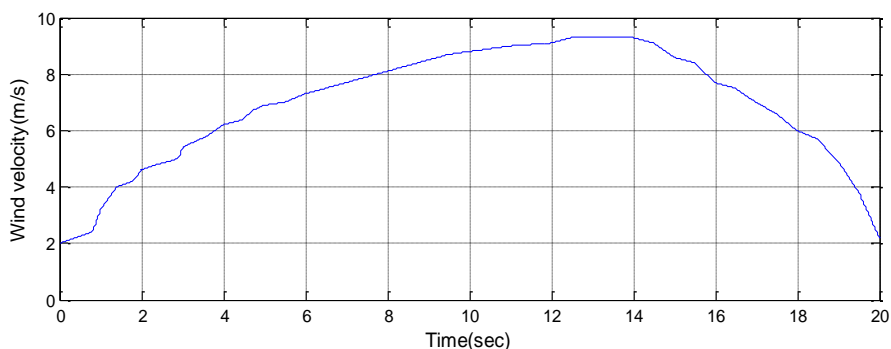


Fig. 5: Wind Speed profile.

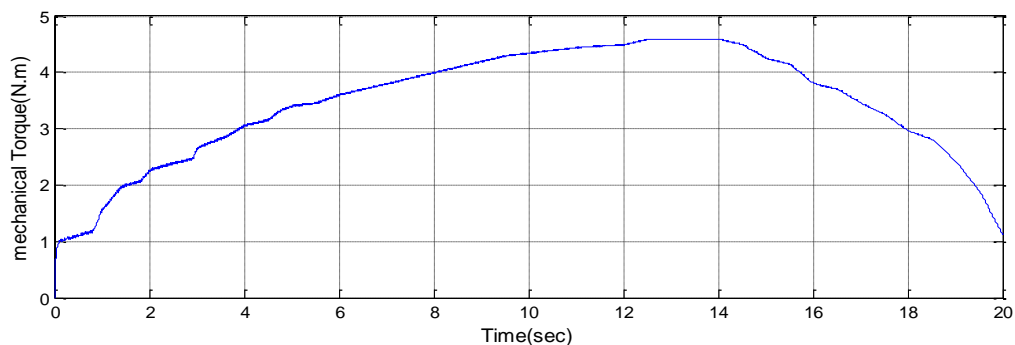
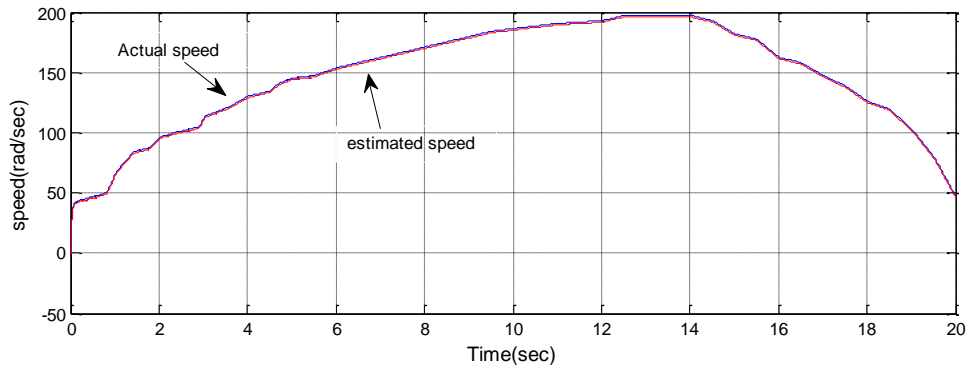
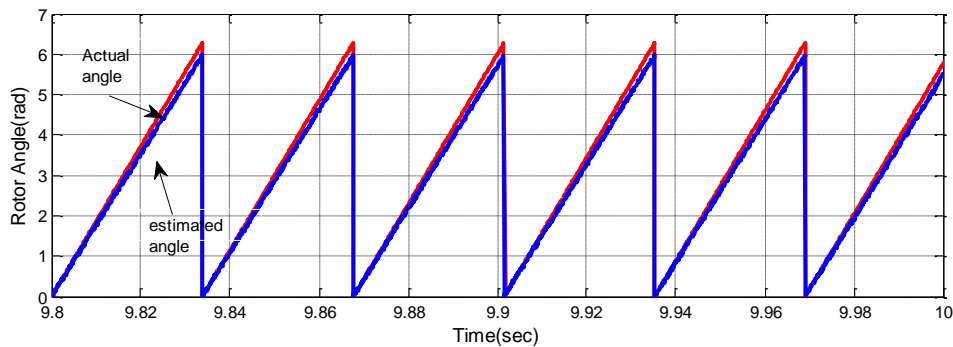


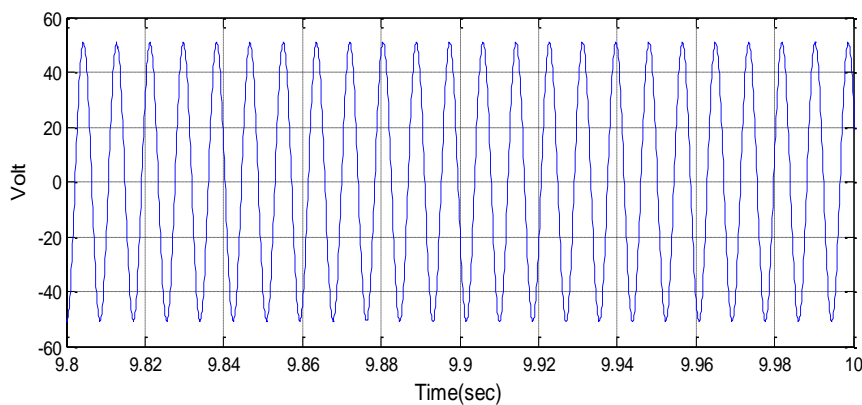
Fig. 6: Mechanical Torque output from turbine (input to generator).



**Fig. 7:** Actual and estimated rotor speed.



**Fig. 8:** Actual and estimated rotor angle.

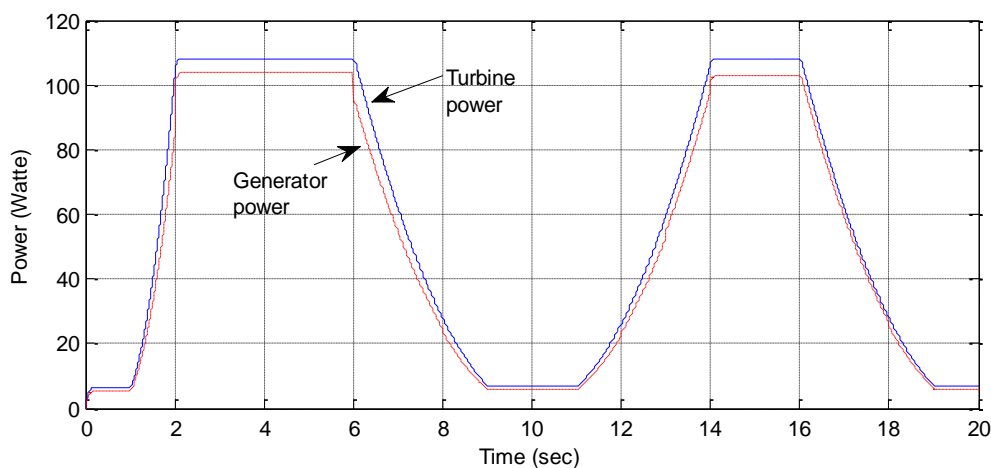


**Fig. 9:** Generated phase A voltage.

## 7.2 Maximum Power Tracking:

As shown in Fig. 2 and according to the equations (2) and (4) the optimal rotational speed  $\omega_{opt}$  of the wind turbine rotor for a given wind speed can be used to obtain the maximum output turbine power. From equation (2) we can regulate the rotational speed of the generator in order to maintain the  $\lambda$  at optimal value at which power is maximum as illustrated in Fig. 1. The wind

speed variation profile is assumed highly random trapezoidal variation. Fig. 10 shows the verification of maximum power tracking control. The wind speed profiles of maximum power tracking control  $P_w$  and the dynamic difference between the turbine power  $P_m$  and generator power  $P_e$  due to the system inertia and friction are also shown in Fig. 9.



**Fig. 10:** Fast power variation tracking control signal of wind profile.

## 8. Experimental Results:

The experimental works are carried out on 2.5KW permanent magnet synchronous generator. The varying speed PM motor drive is used to emulate the dynamic of wind turbine to drive the PMSG directly. And finally the AC power generated PMSG is converted to DC power using three phase rectifier with resistive load. Fig. 11 Shows the experimental setup that was used to validate the proposed algorithm.

The digital signal processor dsPIC30F6010a from Microchip Company are used to control the overall system which has a powerful peripherals specifically designed for motor control (motor control PWM and high speed ADC). ANFIS are implemented as a lookup table in the microprocessor after off line training. The PMSM motor is driven by a pulse width modulated inverter. First the drive speed control loop was measured using a 1024 pulse encoder. The actual and estimated rotor speed as shown in Fig. 12 and Fig.13 respectively are measured using Data monitor and control interface (DMCI) provide with MPLAB software also from Microchip Company which can plot any code variable. This software allows the user to vary the program variable very easy (in our work we use the slider to vary the speed of the motor (turbine) when

the motor run at low speed from standstill to (1000 RPM) which is with a good argument with actual results. Fig. 14 and Fig. 15 show the actual and estimated rotor angle.



Fig. 11: experimental setup.

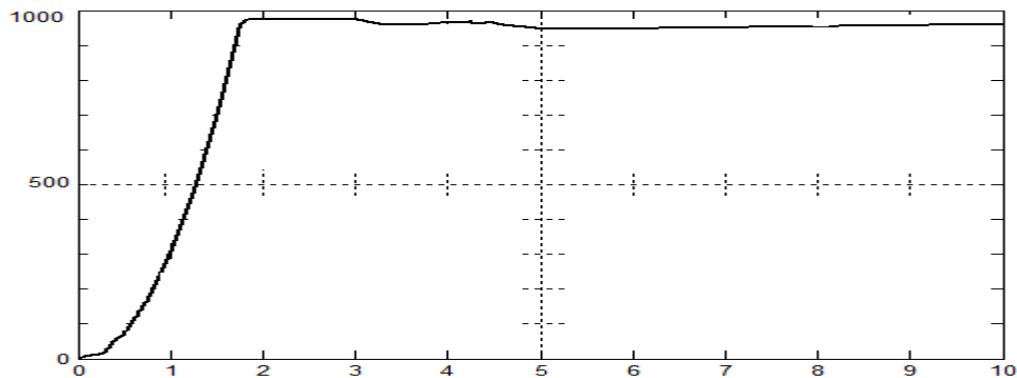


Fig. 12: actual speed(X axis in (sec), Yaxis in(RPM)).

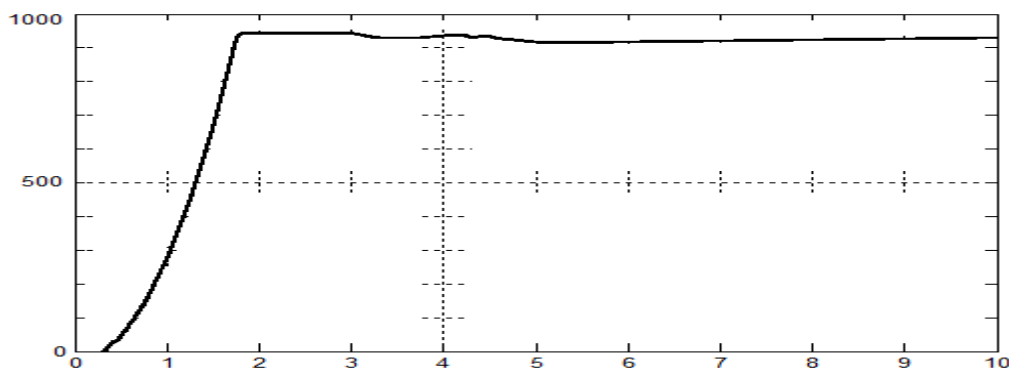


Fig. 13: estimated speed(X axis in (sec), Yaxis in(RPM)).

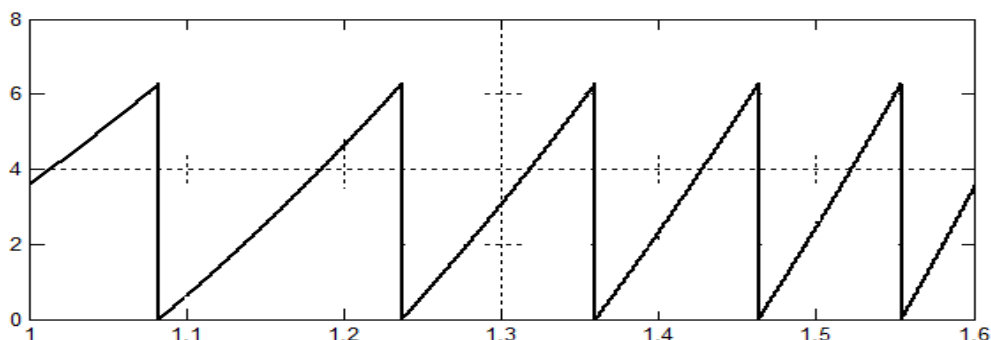


Fig. 14: measured rotor angle (X axis in(sec), Y axis in(rad)).

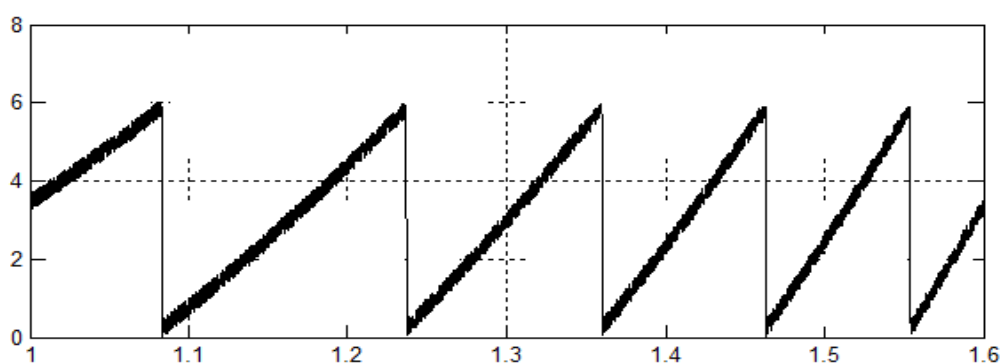


Fig. 15: estimated rotor angle (X axis in(sec), Y axis in(rad)).

## 9. Conclusion:

This paper presented the design of a new intelligent network estimator system for speed and rotor position estimation used in variable-speed wind energy systems. The artificial neural fuzzy network (ANFIS) is trained off line with input-output data set obtained from different operating condition of the generator. Two network has been trained off line used to estimate  $\alpha$  and  $\beta$  circuit back-emf. The data input- output set is obtained from normal operation generator under wide wind speed range. Speed controller sets the generator torque command, which is achieved through PI controller.

The dynamic performance obtained from simulation and experimental results shows an accurate estimation of rotational speed not only in steady state but also for fast input variation.

## Appendix A

The Permanent Magnet synchronous generator has the following parameters:

Rated power: 2.5KW; Max speed :1800RPM;  $R_s = 2.87\Omega$ ;  $L_d = L_q = 5.33mH$ ;  $\lambda_m = 0.375$  wb;  $J = 0.005$  Kg.m<sup>2</sup>;  $D = 0.002$  N.m.s, pole pairs=4.

Wind Turbine Parameters (for simulation):

Base mechanical output power: 3KW; Base wind speed:12m/s; pitch angle=0 (reasonable for low and medium wind speed ); Tip speed ratio=5.8;Air density factor( $\rho \cdot A$ )=0.7716

ABC to Alpha - beta Conversion matrix:

$$\begin{bmatrix} \alpha \\ \beta \\ 0 \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 1 & \frac{-1}{2} & \frac{-1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

Alpha-beta to d q Conversion matrix:

$$d = \alpha * \cos(\theta) + \beta * \sin(\theta)$$

$$q = -\alpha * \sin(\theta) + \beta * \cos(\theta)$$

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